Abstract

This paper models policy making tactics given opportunities to learn from others when it is difficult to know what outcome a policy will produce. I adopt a recent innovation by modeling policy-outcome uncertainty as Brownian motion and apply this formalization to policy diffusion. In addition to incorporating these partially invertible signals, the model merges variables that emerge from previous empirical research with a number of previously unincorporated realities of policy making and learning. These advances include actors’ traits such as similarity and capacity, issue traits such as complexity, a continuous set of policy options, and choices between mimicking and modifying another’s policy. Together, they produce an informational model of diffusion which addresses “who,” “how,” and “when” questions. In addition to offering specific propositions, the model suggests broadening the methods currently used in empirical diffusion research and shifting the focus from the diffusion of specific policies to diffusion in policy areas.

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1 Introduction

Governments, organizations, and individuals regularly make challenging policy decisions without precisely knowing how their choices will produce outcomes. They may have goals they would like to achieve but do not know exactly which actions will best achieve them. Often, many will confront similar policy making challenges at roughly the same time and will have opportunities to learn from others’ choices. These opportunities to learn may enable policy makers to achieve outcomes superior to those they would have achieved acting independently and to do so more efficiently. They may also lead to policy interdependence and similar choices across jurisdictions. This description applies to a wide variety of political and economic decisions which have motivated a large and growing policy diffusion literature. This literature crosses traditional disciplinary and subfield boundaries. It comprises applications to policy choice in cities, the U.S. states, other nations, and even business firms. It highlights many cases in which policies appear to have spread through interdependent mechanisms rather than independent decisions.

This paper adds to this literature by elaborating a highly general, formal, and micro-foundational model of policy diffusion. This model has applications to a wide variety of substantive issues in a range of political settings. These include, organic state and local policy making (e.g. smoking bans), policy making in response to federal mandates (e.g. welfare), national policy making (e.g. democracy promotion programs), implementation of international treaties (e.g. environment), and non-governmental actors’ legal compliance (e.g. affirmative action). The model explicitly treats diffusion as a learning and problem solving process in response to complexity. This “targeted learning” theory of diffusion can help parse mechanisms, explain behavior, and guide future empirical work. In it, actors learn from others to do their best when it is difficult to know what outcome a policy will produce. It delivers predictions about when and how actors will learn from others when confronted with policy making challenges. Most of the existing diffusion literature starts with an actual policy and asks what factors will lead to it spreading. The model below starts with a particular policy area and asks which governments are more likely to make policies independently in it and which are more likely to rely on learning from others. It is more concerned with the content of policies than previous diffusion studies which are limited by focusing on a dichotomous decision between adopting and not adopting. It offers predictions which can help explain a range
of behaviors and distinguish targeted learning from other plausible diffusion mechanisms.

Despite the breadth and depth of interest in the subject, the policy diffusion literature is lacking sufficient general theory. Even the most recent and high profile model (Volden, Ting, and Carpenter, 2008) more clearly undercuts existing empirical findings than points the way toward a series of new inquiries, generalities, and patterns. While recent work has shifted toward theory and mechanisms, the literature has historically been empirical and inductive. It has identified cases in which policies and practices have spread in a variety of settings and proffered a number of plausible explanations for why one’s policy may be influenced by another’s. More recent work, both theoretical and empirical, has sought to generalize and parse these diffusion mechanisms (Dobbin, Simmons, and Garrett, 2007; Shipan and Volden, 2008).

This model advances the existing literature in two distinct but related ways. First, it connects and integrates a number of subsections of the empirical literature. More than more theory in general, the literature would benefit from general theory which can serve as a hub connecting many of the empirical literature’s spokes. The model integrates a number of mechanisms, variables, and considerations that the extant empirical literature suggests are important, but which have largely emerged in a piecemeal fashion through studies of one policy area at a time. These factors include actors’ traits such as similarity and capacity, issue traits such as complexity, and different social learning mechanisms such as imitation. Secondly, the model incorporates, formalizes, and considers other important realities of policy making, learning, and diffusion that have been absent in previous work. It considers a continuous set of policy actions and predicts policy clustering even when policy options are limitless. It also considers learning from others when policy makers can learn something to reduce, but not eliminate, uncertainty by observing another’s action. It does so by applying an innovative formulation of policy uncertainty, Brownian motion (Callander, 2008), to policy diffusion. This model builds on Callander’s work with partially invertible signals by combining it with variables such as capacity and goal similarity to investigate optimal learning from others. Additionally, the model allows a policy maker to either mimic or modify another’s policy, weighs optimal modifying behavior, and characterizes the tradeoffs between modifying and mimicking. Moreover, the model considers learning from one other policy and synthesizing information from a small, but finite (two) number of previous policies. Finally, the model investigates the traits of the other policy makers that have already acted. It analyzes how these actors’ goals, and the
possibility that they make policy errors, affect how another will learn from them.

This approach offers a number of intuitive yet unexplored insights into diffusion. For example, it suggests that policy makers with more capacity are more likely to make policy decisions independently while those with less capacity are more likely to produce diffusion by relying on learning from others. It also suggests that policy makers are more likely to imitate policies when learning from those with similar goals and when issues are more complex, and more likely to make adjustments to existing policies when learning from those that are less similar and when issues are relatively straightforward. More generally, this type of theorizing can help us study when and how policy choices will be interdependent as a function of actor and issue traits. This is a substantial advance over trying to measure interdependence among policies that we know became popular.

The model is very general. While its components, actions, and variables are most connected to policy diffusion among governments it is also applicable to business firms and even individuals. Because the model is so general, it can incorporate “politics” in a couple of ways. First, the general formulation of policy-outcome uncertainty can easily apply to uncertainty between policies and objective policy outcomes (e.g. economic growth, health care delivery, innovation etc.), uncertainty between policy and political outcomes (e.g. approval ratings, campaign donations), or a combination of the two. A model of policy makers making decisions about policies they can control to produce outcomes that they are less confident about applies to policy and politics at all levels and substantive areas. Secondly, the model may also be thought of as a thorough investigation of the “whys” and “hows” of the “external determinants” part of many policy diffusion studies. These “external determinants” are usually vague, underspecified, and overly focused on factors such as “geographical proximity” (Berry and Berry, 1990).

After situating the model in the literature, I provide an overview of it, and then describe, explain, and justify its assumptions. Next, I derive the expected policy outcome and the expected utility of the model’s four primary decision making actions. After briefly considering the simplest case in which one policy maker acts alone, I analyze decisions about who to learn from, and how to use what one learns in cases with two and three actors choosing policies. Finally, I discuss some of the model’s implications for empirical work more concretely. These implications include specific patterns, mechanisms, and associations that empirical work should be able to identify. More generally, the model suggests that empirical diffusion work should broaden its methods and
approaches. Focusing on the diffusion of a particular policy, as nearly all studies do, instead of investigating diffusion in particular policy areas misses a lot of important variation.

1.1 Background: Policy Diffusion and Policy Making

Much of the extant diffusion literature is empirical and inductive. It highlights the adoption of similar policies in many settings including sub-national governments in the U.S. (Berry and Berry, 1990; Grossback, Nicholson-Crotty, and Peterson, 2004; Shipan and Volden, 2006, 2008; Volden, 2006), international relations (Meseguer, 2006; Weyland, 2005), and business firms (Strang and Still, 2004; Strang and Macy, 2001). While most diffusion studies focus on policy making, similar processes apply to legal and policy implementation (e.g. Barnes and Burke, 2006; Dobbin and Kelly, 2007; Edelman, 1992; Gould, 2005) where private actors are vital cogs in policy making in practice (Dobbin and Sutton, 1998; Farhang, 2008). As Elkins and Simmons (2005) note, some use the term “diffusion” to refer to the outcome where an action spreads for any reason (including independent choices), while others use it to refer to a process where interdependent decisions lead to the spread of policies. I use the term in the second sense by focusing on mechanisms, in this case incomplete information, which cause policy diffusion and commonality.

Given the interest in the ideas, and their broad applicability, there are fewer general theories of diffusion than one might expect. The model below joins recent work that analyzes diffusion mechanisms deductively by beginning with rigorous micro-foundations (Braun and Gilardi, 2006; Meseguer, 2004; Volden, Ting, and Carpenter, 2008). The literature has more effectively generated diffusion findings and mechanisms than it has parsed them. Explanations for diffusion include informational accounts in which policies diffuse because actors learn something about their benefits from others’ experiences, competitive accounts in which actors follow others to maintain advantages or parity, coordination accounts in which there are tangible benefits to conforming to a common standard, and adaptive accounts (Elkins and Simmons, 2005), including variations on “normative isomorphism” (DiMaggio and Powell, 1983) in which policies diffuse because it is safer or more legitimate to follow the crowd. The empirical literature has proceeded by identifying a policy that became popular and applying a statistical technique such as event history analysis to identify the influence of an interdependent variable of interest (often related to geographic proximity) on a political actor’s propensity to make a binary adoption choice (Berry and Berry, 1990).
Recently, empirical scholars have shifted attention measuring and distinguishing different diffusion mechanisms (Shipan and Volden, 2008; Tyran and Sausgruber, 2005).

To date, one of deductive theory’s biggest contributions has been demonstrating how ostensible policy diffusion could actually result from actors learning from themselves (Volden, Ting, and Carpenter, 2008). Other theoretical contributions focus on different levels of rationality in policy learning (Meseguer, 2004; Weyland, 2005). The model below begins to fill the substantial and conspicuous theoretical gap in this large and broadly applicable literature. It does so by incorporating a number of traits and dimensions that the empirical policy diffusion literature has focused on but not connected. The traits it incorporates are related in one way or another to informational accounts of policy diffusion which pose uncertainty about policies and their outcomes as the foundation of diffusion mechanisms.

The empirical literature has identified and focused on a number of traits which appear connected to policy diffusion in at least some contexts. It has done so in a piecemeal way. Most papers focus on one or two factors in one substantive policy area. Many have emphasized social learning as the basis of diffusion. These empirical accounts of diffusion by learning include learning from geographical neighbors (Berry and Berry, 1990; Mooney, 2001), learning from effective policies (Volden, 2006), learning from ideologically similar states (Grossback, Nicholson-Crotty, and Peterson, 2004), and learning from more observable policies (Volden and Makse, 2010). Relatedly, empirical and theoretical work has focused on different ways of learning including emulating successful policies (Volden, 2006), imitating policies irrespective of quality (Karch, 2007; Shipan and Volden, 2008), bayesian learning based on observing all others’ experiences (Meseguer, 2004), heuristic learning in which actors rely on shortcuts such as availability (Weyland, 2005), and learning in information cascades (Bikhchandani, Hirshleifer, and Welch, 1992, 1998). Recent work has also focused on isolating learning from other diffusion mechanisms such as competition and coercion. Tyran and Sausgruber (2005) found evidence of emulation in a controlled laboratory experiment in which they isolated its effect. Shipan and Volden (2008) use observational data concerning smoking policies and find evidence of diffusion by imitation, emulation, competition, and coercion in the same policy case.

The model below fits squarely into this diffusion as learning literature. It does so in the broad sense by treating informational problems and learning from others as the basis of policy diffusion.
It also connects in a narrower sense by including “imitation” as an action and focusing on the traits of other governments that a policy maker may consider learning from. While others have included “imitation” as a specific incarnation of social learning, they have not specified when we should see imitation and when we should see other uses of others’ policies such as “modification.” Additionally, “imitation” can refer to imitation for the sake of similarity or imitation as a shortcut in lieu of learning. In the model, imitation is one way to use what one learns from others in a learning framework. Imitation can still be a learning tactic even when one cannot actually wait to observe a policy’s quality in practice.

The model incorporates and connects other key sources of variation that have appeared in the empirical literature but have remained theoretically unconnected. The first of these variables is goal similarity between an actor making a policy decision and those that have already made decisions (Dolowitz and Marsh, 1996; Grossback, Nicholson-Crotty, and Peterson, 2004; Volden, 2006; Volden, Ting, and Carpenter, 2008; Volden and Makse, 2010). This similarity concept is highly generic in the model though other empirical work has focused on narrower conceptions of similarity. This work has demonstrated, for example, a link between ideological similarity and policy diffusion (Grossback, Nicholson-Crotty, and Peterson, 2004). In contrast to the existing literature, the model considers precisely why similarity should matter, how goal similarity interacts with other factors, and when it will be the primary diffusion driver.

In addition to variations in similarity, the model accounts for variations in capacity. Empirical work has focused on similar concepts such as “professionalism” and “attention” (Volden, 2006), and “size” (Shipan and Volden, 2008). Professionalism appears to aid diffusion while smaller size leads to imitation. As with similarity, the literature has insufficiently delineated the precise mechanisms though which capacity should affect diffusion. This is partly a result of focusing only on policies after they appear to have diffused. The model suggests that one role capacity plays is that it reduces the likelihood that some actors will adopt diffusing policies and instead will make choices independently. It also suggests that even if higher capacity governments use diffusion tactics (learning from others) more than lower capacity ones in an absolute sense, lower capacity policy makers will be more influenced by others’ policies in a relative sense.

Lastly, the model builds on recent work that has advanced the literature by considering variations in issues and policies in addition to variations in governments’ traits (Nicholson-Crotty,
These traits include “observability” (increases diffusion) and “trialability” (decreases diffusion) (Volden and Makse, 2010). They also include “complexity,” which is a central source of variation in the model. The model’s conception of complexity concerns the complexity of the issue area and is more similar to Nicholson-Crotty’s (2009) issue based complexity which slows diffusion than it is to Volden and Makse’s (2010) which is tied to a particular policy innovation and reduces diffusion. Moreover, the model implicitly focuses on situations in which “trialability” is low such that policy makers cannot wait to observe the results of their own or others’ experiments. Instead, they use what they know about other policy makers as a cue about a policy’s fit and quality.

The model makes additional theoretical advances beyond incorporating these previously unconnected findings and variables that have emerged from empirical work. It differs from Volden, Ting, and Carpenter’s (2008) recent model by allowing an infinite set of policies, implementing a broader notion of policy uncertainty, allowing actors to modify rather than outright adopt known policies, and by focusing on questions of who learns, from whom, and how? Decision makers in their model are making tradeoffs between a finite set of policies’ ideological dimensions (liberal conservative), and a valence effectiveness attribute. In the model below, actors are searching for policies to best satisfy a flexible and malleable set of goals and constraints. Moreover, policy space is continuous and thus the policy clustering it predicts is not imposed by construction. Lastly, though crucially, the model allows and considers the possibility that actors do not simply adopt existing policies off the shelf. It allows them to alter existing policies and evaluates the tradeoffs between mimicking and modifying.

The model’s other innovation is its application of signals which are always partially invertible in continuous policy space (Callander, 2008) to policy diffusion. Many models of policy-outcome uncertainty, including some canonical political science models of expertise in principal-agent problems, implicitly assume that signals are fully invertible (Gilligan and Krehbiel, 1987, 1989, 1990). Actors observing others can reverse engineer the uncertainty and private information out of actions and apply this information their own decisions. They can thus eliminate uncertainty from future decisions by observing one action and the outcome it produces. Partially invertible signals are more consistent with many situations. Often, knowing another’s action and her goal tells a second actor something, but not everything, about the first’s private information. Recently,
Callander (2008; 2010) has readdressed the delegation problems which motivate the fully invertible uncertainty representation along with other questions of policy experimentation. He reformulates policy-outcome uncertainty by modeling the shock as Brownian motion. I apply this innovative formalization which nicely captures many elements of complicated policy choices and policy learning to the policy diffusion context. This technology enables incorporating many of the advances described above, such as similarity, continuous choices, and modifying in an intuitive and parsimonious way. In the delegation models, agents have more expertise than their principles, and in the policy experimentation context, they can either keep their existing policies or try something different after learning from their own policies (Callander, 2010). In the targeted learning model, some policy makers have more information than others, and actors can either adopt others’ policies or modify them to make new ones.

Other models of social learning and information transfer, particularly information cascade models (Bikhchandani, Hirshleifer, and Welch, 1992, 1998), have demonstrated the importance of information invertibility and how information transfer affects outcomes. In these models, signals quickly shift from invertible, to partially invertible, to non-invertible as more and more actors take actions based less and less on their private information. The model below is more concerned with problem solving strategies in which signals are always partially invertible. Cascade models are primarily concerned with the dynamics of information transfer as signals become less and less invertible. Relatedly, the model’s focus is one actor facing a decision after others have faced similar, but potentially different, decisions. It is less concerned with actors facing the same choice in sequence. Finally, the theory’s incorporation of infinite policy options and analysis of mimicking and modifying others’ actions also differentiates it from these previous models with partially invertible signals.

2 Model Overview

The model considers the behavior of N policy makers (zi; i ∈ 1...N). For simplicity, as in many policy models, governments are treated as unitary actors. Each government (zi) faces a policy challenge and must contemplate a response. It can either enact a new policy (pi) in R^1 or retain the status quo (sq). The status quo produced an acceptable outcome previously, but may not
anymore due to exogenous changes which prompt the policy decision. Often, the status quo will be having no policy at all. The changed circumstances create uncertainty about the new outcome that the old status quo produces. The new status quo outcome varies by actor depending on their previous activities. The same changing circumstances (or legal change) might be a small shock to some and a large one to others.

Each policy $p_i$ produces an outcome $o_i \in R^1$. Each government has an ideal outcome ($o_i^*$) and quadratic loss preferences around it. Because the world is complicated, and instituting policies is an inexact science, the mapping from policies to outcomes is uncertain. For example, a policy might be set of production and/or consumption incentives to encourage replacing old appliances with energy efficient ones. The outcome this policy produces might be the number of appliances actually replaced or the amount of energy saved per year in the jurisdiction.

Policy makers will only have beliefs about which policies produce which outcomes. A policy mapping function $\psi(p) \in \Psi$ maps each policy ($p$) to an outcome ($o$). I represent the policy mapping function, and thus the policy uncertainty, by Brownian motion (Callander, 2008). Intuitively, Brownian motion is a path of random fluctuation with an underlying linear trend ($\mu$). It zigs and zags noisily while “drifting” on average along the slope $\mu$. Actors know that the policy map is a Brownian motion with drift $\mu$ and variance $\sigma^2$, but they do not know the realization of $\psi$ that nature has drawn.\footnote{As Callander (2008) notes, Brownian motion usually represents movement through time. In this case, there is no time element. Once the path is realized, it is the policy map which converts policies to outcomes.} This representation of uncertainty is partially invertible (see below). By observing one policy-outcome pair, an actor learns exactly one point through which the path passes. This reduces, but does not eliminate, uncertainty about other policies.

To observe the map’s full realization, one must invest in costly, potentially prohibitively costly, research $R_i$ to learn $\psi(p)$. Research costs are actor specific parameters which vary inversely with capacity. High capacity policy makers become informed relatively efficiently. Investing in research will enable an actor to set $p_i = p_i^*$ to produce $o_i = o_i^*$ which is its ideal outcome. Later I consider a case in which actors may still make errors after investing in research. Actors also know others’ ideal outcomes and the distance (the difference) between their own ideal outcome and another’s ($\Delta_{ij}$). They thus know how similar other governments are to themselves, and how well another’s
ideal policy would fit their own goals and constraints (see below). Much of the analysis considers four basic options: 1) maintain the status quo, 2) research and learn the policy mapping, 3) follow another’s policy by simply implementing it, and 4) alter another’s policy by learning something from it and then making changes to move policy toward (hopefully) one’s own ideal outcome. At the end, I analyze learning from more than one other actor and actors who fail to implement their ideal policies.

3 Elaboration of Key Assumptions

To supplement the overview, this section further details, explains, and justifies a few of the model’s key assumptions. These key assumptions include the characterizations of utility and uncertainty, the actions available to the actors, and the information that is common knowledge. In elaborating these assumptions I cite evidence from conversations with college and university attorneys to bolster their veracity. In these conversations the attorneys described how their institutions make policy choices in response to vague and ambiguous laws. This setting is different than legislative policy choice for example, but some of the basic policy making tactics and factors should be comparable. These interviews at least suggest that some of the model’s innovations and key assumptions and actions are consistent with practice on the ground.

3.1 Spatial Utility

Each policy maker has goals that it would like to achieve or constraints it must meet. Thus, each has an optimal outcome \( o^*_i \) which balances all relevant considerations. Each also has quadratic loss preferences around this ideal outcome. \( U_i(o_i) = -\gamma_i(o_i - o^*_i)^2 \) where \( o_i \) is \( z_i \)’s policy outcome and \( o^*_i \) is its ideal outcome. The quadratic loss from the gap between the optimal outcome and the realized one is multiplied by a parameter \( \gamma_i \). This parameter represents the importance of the decision to the actor or how much it has at stake. The same deviation from \( o^*_i \) will be more costly for a larger \( \gamma_i \). Risk aversion and quadratic loss preferences, which are canonical but not required (Bendor and Meirowitz, 2004), in many policy choice models, do play an important role in the mimic vs. modify tradeoffs analyzed below. If large errors are more costly and undesirable there are conditions under which policy makers will prefer to imitate an imperfectly fitting policy.
3.2 Partially Invertible Policy Uncertainty

Each policy maker does not know exactly which policies produce which outcomes. The interviews bolster the veracity of this underlying assumption. Practitioners view many of these policy decisions as challenges wrought with complexity and uncertainty. They often said that legal policy making was similar to other difficult problems their organizations face. As one attorney said, “we think about how to approach these problems in a systematic way. There is so much arcana, so much to know. No one can know all of the details about what to do.”

To represent this uncertainty, I assume that a policy process $\psi : P \rightarrow O$ maps policy choices (P) on the real line to policy outcomes (O) on the real line. The canonical process (e.g. Gilligan and Krehbiel, 1987) in policy making models assumes that policies produce outcomes through an unknown shock $\omega$ drawn from a uniform distribution $[-\lambda, \lambda]$ such that policy p produces an outcome $o = p + \omega$. As Callander (2008) argues persuasively, this assumption inadequately captures policy complexity in many instances. Its main shortcoming is that it is perfectly invertible. If one actor becomes informed and learns $\omega$, others can perfectly infer $\omega$ from the gap between the informed actors’ ideal outcome and her policy choice. While signals are also partially invertible in cascade models (Bikhchandani, Hirshleifer, and Welch, 1992, 1998) these models do not directly apply to one actor trying to import a partially invertible signal from another’s different decision context to her own.

For example, consider a professor trying to write a statistics exam that will take students a certain amount of time. We might imagine that the time it takes the students to complete is some function of how long it takes the professor to answer the questions. If this “shock” is constant (e.g. it takes students 30 minutes longer than it takes professors to complete the same exam), than the professor can always plan accurately after administering or observing one exam. In this case, observing the constant 30 minute shift is enough for the professor to accurately predict the amount of time any exam will take. She just needs to add 30 minutes to the time it takes her. Many real world policy choices are more complex. For example, if different types of exam questions lead to different time gaps, then the canonical model would break down in the example as the shift would no longer be constant. The canonical representation essentially assumes that the world is complex, but that actors can reverse engineer one policy to learn about all policies. The Brownian
motion representation allows the professor to utilize knowledge of the average relationship between student and teacher test taking times, while incorporating uncertainty and allowing it to vary with other factors.

The targeted learning model adopts Callander’s representation of uncertainty. It assumes that the policy process $\psi$ is only partially invertible. That is, an uninformed government can learn something about it to reduce some uncertainty by observing an informed government, but it cannot perfectly learn. More specifically, I assume that the policy process is a Brownian motion with drift parameter $\mu$ and variance $\sigma^2$ which are common knowledge. Policy makers know the underlying linear trend and the variance around it (figure 3.2). Observing an informed government’s policy choice reveals one point through which the function passes. To help with intuition, consider a boat floating in the ocean. We may know that it is drifting northeast with the underlying current, but that stray waves, shifting puffs of wind, and other factors jostle it back and forth. It does not move in a straight line, but it does move northeast on average. If we spotted it once, and knew a point through which it passed, we would have a better idea where to look for it later. We would expect to find it northeast of where it was spotted, but because the waves and wind also affect its path, we should not expect to find it due northeast.

Figure 1: Example of Brownian motion of slope $\mu$ with one known policy-outcome pair $(p_1, o_1)$

More formally, after observing one policy mapping, e.g. policy $p_j$ produces outcome $o_j$ ($\psi(p_j) = o_j$), an actor has updated and improved beliefs about other policies. Specifically, knowing that
\( \psi(p_j) = \alpha_j \), another policy \( p \)'s expected outcome and its variance are:

\[
\text{Expected Outcome: } E[\psi(p)] = \alpha_j + \mu(p - p_j)
\]

\[
\text{Variance: } \text{var}[\psi(p)] = |p - p_j|\sigma^2
\]

This model of policy uncertainty is not only mathematically tractable, but has an intuitive interpretation (Callander, 2008). The expected value of policy \( p_2 \) is just the slope of the line (the drift) multiplied by the distance from the known point policy \( (p_1) \) to policy \( p_2 \). The variance is growing proportionally to the distance to the unknown policy. There is more uncertainty the further away one moves from a well understood policy to set a new one. The ratio \( \frac{\sigma^2}{|\mu|} \) indicates policy complexity. The larger the ratio, the less one learns about the full mapping from observing one policy-outcome pair. Additionally, this model of policy uncertainty allows actors to know roughly which direction to move from another’s policy to get to their own ideal outcome, and how far they should move. This nicely approximates many real life situations. We often may not know exactly how policies produce outcomes, but we do have a sense of how to tweak an existing policy to better achieve different goals.

### 3.3 Knowledge of Others’ Outcome Goals

While \( z_i \) does not know the exact mapping from policy choice to outcomes, it does know others’ outcome preferences (\( o^*_j \) for all \( j \)). Knowing its own outcome preferences and another’s, a policy maker knows the difference between them (\( \Delta_{ij} = |o^*_i - o^*_j| \)). This distance can be thought of as goal similarity and may comprise factors such as population demographics, economic conditions, political ideology, and others.\(^2\) Small \( \Delta \) implies similar goals. In most contexts, policy makers will generally know how similar they are to others. They will thus know, or at least have strong

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\(^2\)While others, (e.g. Grossback, Nicholson-Crotty, and Peterson, 2004; Volden, 2006) note associations between similarity and policy adoption in diffusion studies, they have not proffered explicit predictions about variation in its importance in a learning setting. Additionally, in a recent review article, Dobbin, Simmons, and Garrett (2007) include notions of peer groups in their discussion of “constructive” diffusion” which is more a more sociological mechanism than this model’s. Here, peers are important because they allow credible, though imperfect, inferences
beliefs about, how well another’s optimal policy is likely to work for them. More generally, it is reasonable to expect that policy makers have a strong sense, without knowing anything about the actual policy, which other actors’ ideal policies will be relatively good fits.

The interview evidence also bolsters this assumption. Attorneys spoke at length about the other colleges and universities they could look to for ideas. Many have lists of similar peer institutions and others which they know are less similar. Some referred to keeping up with “your group.” An institution’s list of 10 or 12 (sometimes more) “peer” or “comparator” schools is usually predictable. This list of schools is often closely aligned with athletic conferences and other collections of institutions that have much in common with each other.

4 Actions and Utility

Conditional on having others to observe, the model assume that a policy maker has four possible actions available to it. It will only have two tactics if there are no other policies to observe. 1) It can maintain the status quo policy. 2) It can invest in costly research to gather more information, eliminate uncertainty, and tailor a custom policy to achieve its ideal outcome. 3) It can mimic and follow another’s policy. 4) It can modify by starting with another’s policy but then altering it to move closer to its own ideal outcome. Mimicking is really a special case of modifying in which the optimal modification is no modification. In some applied cases it may make sense to think of mimic vs. modify as a dichotomous choice whereas in others the more substantively applicable question may be one between modifying a little (approximately “mimicking”) or modifying a lot. Unlike the Volden, Ting, and Carpenter (2008) model, I do not consider learning from one’s own experience and focus instead only on the ins and outs of learning from others. Callander (2010) investigates learning from one’s own policy experiments in the Brownian motion framework in great detail.

Some of these tactics build on the existing literature while others extend it substantially. More specifically, while many (e.g. Berry and Berry, 1990) speak to informational factors and learning in their “external determinants” (diffusion) of policy, they do not focus on capacity and the ability to make good policy choices independently when considering “internal determinants.” This model’s about policies’ efficacy conditional on traits and circumstances.
“tailor” option puts independent policy making into an informational context along with external policy influences. Moreover, while the mimic option parallels other diffusion studies that include “imitation” as one form of social learning, the “modify” option, along with considering the tradeoffs between the two, is more innovative.

The interview evidence supports the inclusion of these four actions. The respondents frequently mentioned independent analysis, but they mentioned it as something they rarely do. Nearly all said “we do not reinvent the wheel.” More importantly, the interviews suggest that a model of learning from others should incorporate both the “mimic” and “modify” options. The conditional use of these two tactics appears to be one of the more interesting elements of policy learning and diffusion. Evincing the use of “mimicking,” one attorney said, “I have no problem plagiarizing, picking and choosing parts of other places’ policies, and I have no problem when they do the same to us.” On the other hand, many spoke of “modifying” others’ policies, especially those known to come from less similar institutions. For example, one said “you look at what they’re doing, but may have to tailor to the different circumstances.”

Unpacking the possible actions first makes it easy to solve for the optimal tactics in different scenarios later. In general, the expected utility of a tactic is $-\gamma_i E[(O_j - o^*_i)^2]$ or $-\gamma_i [(E(\psi(p_i)) - o^*_i)^2 + Var(\psi(p_i))]$. Specifically, the four possible actions and utilities are:

1. **Status Quo (sq):** Do nothing and maintain the status quo (even if the status quo is not having a policy). The more dramatic the external shock, the worse the old status quo policy will be. By construction, the status quo policy produces an outcome (q) drawn from a symmetrical distribution around 0 with known variance. For simplicity, I follow Callander (2008) and assume that q is drawn from a uniform distribution on the interval $[-c_i, c_i]$ where the width of the interval corresponds to the uncertainty about the old policy in the new environment.\(^3\) Therefore, $z_i$’s expected utility from maintaining the status quo ($EU_i(sq)$) is:

$$EU_i(sq) = -\gamma_i \frac{c_i^2}{3}$$  

\(^3\)I assume that there is a delay in observing a policy’s outcome such that one does not immediately learn the policy-outcome pair associated with the status quo when the law changes. This is analogous to no or low “trialability” (Volden and Makse, 2010)
This is the reserve utility which a government will get it unless it takes another action. The width of the $c_i$ interval depends on the shock associated with the change in the policy environment. The more circumstances change, the less tenable the previous status quo will be.

2. **Tailor**: Pay the research cost and learn the policy mapping function. Implement the policy that produces outcome $o_i^*$.  

$$EU_i(tailor) = -R_i$$  

(4)

When tailoring, a policy maker invests in costly research to learn the state of the world and makes an independent policy which produces its ideal outcome. (Later I consider imperfect research which does not lead to achieving the ideal point). Tailoring may include things like cost benefit analysis, hearing expert testimony, commissioning reports and other such methods. For now, the utility of tailoring is simply the cost of learning the policy mapping (there is no spatial utility loss since I assume tailoring leads to perfect policies). This cost is decreasing with legal capacity.

3. **Mimic**: Implement the same policy $p_j$ as another government $z_j$ and get its outcome. This government will have done research, learned the policy mapping, eliminated the uncertainty, and made policy to produce its own ideal outcome $o_j^*$. Mimicking produces an outcome exactly $\Delta_{ij}$ away from one’s own ideal point because the government that follows gets the others’ ideal outcome.

$$EU_i(mimic_j) = -\gamma_i \Delta_{ij}^2$$  

(5)

4. **Modify**: Observe another’s policy ($p_j$) and outcome ($o_j$). Attempt to implement a policy closer to one’s own ideal point after incompletely learning about the policy map. Start with the others’ policy and then make changes to it. To use a familiar example, an instructor teaching an introductory class about congressional politics for the first time might find a more advanced syllabus and then replace some of the more technical works with simpler
This tactic is closely related to “experimentation” in Callander’s (2010) model. In his model, one learns from one’s own policy choices and may experiment by moving away from a policy outcome pair that it has already produced to try to get closer to achieving its ideal outcome. Modifying another’s policy is similar to experimenting in his model when beliefs are “open ended.” Assuming, without loss of generality (the details of the “modify” derivations are in the appendix), that $\mu$ and $(o_i^* - o_j^*)$ (the distance $\Delta_{ij}$ between i and j’s ideal outcomes) are positive, the expected utility of implementing policy $p_i$ which produces outcome $o_i = \psi(p_i)$ after observing that $\psi(p_j) = o_j^*$ is:

$$EU(p_i) = -\gamma_i[\mu(p_i - p_j) - \Delta_{ij}]^2 - \gamma_i(p_i - p_j)\sigma^2$$

(6)

This is the general expression for the expected utility of modifying. When modifying, a policy maker still has choice about which policy to implement. Thus, we must solve for the expected utility of the optimal altered policy given what the policy maker knows at the time it must make a decision. This optimal altered policy is denoted $\hat{p}_i^*$. We solve for it by finding the $p_i$ that maximizes equation 6. The best modified policy, $\hat{p}_i^*$, given available information is:

$$\hat{p}_i^* = p_j + \frac{\Delta_{ij}}{\mu} - \frac{\sigma^2}{2\mu^2}$$

(7)

Intuitively, this expression and proposition says that the optimal modified policy will be closer to the well understood one than it would be without uncertainty. The $p_j + \frac{\Delta_{ij}}{\mu}$ component is exactly what one would do to get to $o_i^*$ if the policy mapping was linear with slope $\mu$. Because of the uncertainty and risk aversion (quadratic loss), simply extrapolating from a known point is not the optimal way to modify. Instead, a policy maker should shade their policy toward the safe and known one. Formally, this manifests in subtracting the variance term which moves the optimal altered policy closer to the known one. Since the variance is multiplied by the distance of the outcome $o_i = \psi(p_i)$ after observing that $\psi(p_j) = o_j^*$

\footnote{While the distinction between following and altering is clean in the model, it is murkier in reality. A continuum ranging from direct cutting and pasting to radical re-engineering is probably more accurate. Parsing following and altering empirically is likely much more difficult than thinking of instances where we have used the two tactics in our own lives.}
jump between the two policies, one should shorten that jump to reduce the cost of uncertainty. Modifying a known policy too much is too risky especially when issues are complicated. The more complex the issue, the less one should wander from a well understood policy’s safety. Thus, altered policies should be relatively conservative (closer to the known policy than the ideal point gap suggests they would be without uncertainty) particularly when issues are more complex.

**Proposition 1.1** When modifying, choose the optimal policy according to equation 7. To get to this optimal policy one should move in the direction of one’s ideal from the existing policy but by an amount less than the difference in goals (|Δ|). The distance one should move from the known policy will decrease with issue complexity making modified policies more “conservative” in more complicated environments.

We can then solve for the expected utility of altering by implementing the optimal policy \( \dot{p}_i^* \). We substitute \( \dot{p}_i^* \) from equation 7 into equation 6 (details in the appendix) to get the expected utility of implementing the best altered policy after learning one policy-outcome pair:

\[
EU(\dot{p}_i^*) = -\gamma_i \left[ \frac{\Delta_j \sigma^2}{\mu} - \frac{\sigma^4}{4\mu^2} \right]
\] (8)

The remainder of analysis derives conditions for when one would use one or another of these tactics as a function of other variables. The intuition behind these four options is straightforward. Since mastering a policy area wrought with complexity and ambiguity is costly, the propensity to do so depends on how efficiently one can tailor. Those with more capacity or more to lose by not learning, are more likely to invest. Others cannot afford to do so but may benefit from the fact that there are others facing the same challenges. One can adopt a policy which another has enacted, or begin with another’s policy, learn from it, and then move toward one’s own ideal outcome. The former offers the security of a proven policy. One that is well understood and has been “de-bugged.” The latter offers the ability to apply what one learns from another to customize their policy and improve the fit. The downside of the first is that the policy which works well for another’s circumstances might not fit one’s own very well. The downside of the second is that one can easily make errors trying to translate another’s ideal policy to fit its own situation.

Ideally one can find a well informed peer who has the same goals. Frequently this is not the
case. Often, decisions will require tradeoffs between the security of a proven policy, and the risks of trying to improve one that was designed for a different context. Before beginning to compare the tactics in different situations, table 1 summarizes the four general decision tactics, associated utilities, and policy outcomes. The expected outcomes and associated utilities in table 1 allow us to solve for the optimal tactic in different situations as a function of policy makers’ and issues’ traits. The ensuing sections elaborate this analysis beginning with a simple one player case (no learning) and concluding with three player cases with and without perfect information transfer.

Table 1: Summary of decision tactics and their associated expected outcomes and utilities.

<table>
<thead>
<tr>
<th>Tactic</th>
<th>Expected Utility</th>
<th>Policy Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Status Quo</td>
<td>$-\gamma_1 \frac{\sigma^2}{\mu}$</td>
<td>$q$</td>
</tr>
<tr>
<td>Tailor</td>
<td>$-R_i$</td>
<td>$\psi(p_i^<em>) = o_i^</em>$ (one’s ideal outcome)</td>
</tr>
<tr>
<td>Follow</td>
<td>$-\gamma_i \Delta_{ij}^2$</td>
<td>$\psi(p_j) = o_j^*$ (the other’s ideal outcome)</td>
</tr>
<tr>
<td>Alter</td>
<td>$-\gamma_i [\frac{\Delta_{ij} \sigma^2}{\mu} - \frac{\sigma^4}{4\mu^2}]$</td>
<td>$\psi(p_i^*) = p_j + \frac{\Delta_{ij} \sigma^2}{\mu} - \frac{\sigma^4}{2\mu^2}$ (the best (expected) altered policy option)</td>
</tr>
</tbody>
</table>

5 One policy Maker (or N Policy Makers Acting Independently)

First, consider the simple case where there is only one policy maker. This is similar to a case in which many governments act independently and cannot observe each other. This case is simply the trade-off between maintaining the status quo and investing to learn the policy mapping. This simple analysis can begin to help us identify governments and other policy makers that are relatively likely to innovate and design their own policies. Those that do not fit in this group are those that are more likely to rely on social learning tactics to make difficult policy decisions and who may not make new policies unless they have models to learn from.

Players: There is only one player, $z_1$, with ideal outcome $o_1^*$, $\gamma$ parameter $\gamma_1$, status quo outcome interval $[-c_1, c_1]$, and research cost $R_1$.

Sequence: 1) The world changes. 2) Nature draws the realization of the policy map. 3) $z_1$ chooses whether to maintain the status quo or invest to learn the full policy mapping. 4) $z_1$ realizes utility.

Analysis: Since there is only one player, the mimic and modify options are irrelevant. Tailoring
(equation 4) is preferred to the status quo (equation 3) when:

\[ R_i \leq \gamma_i \frac{c_i^2}{3} \]

Intuitively, a government’s likelihood of tailoring a new custom policy is increasing in capacity (decreasing research costs R), and increasing in the importance of the issue (\( \gamma_i \)). It is also increasing in the amount that exogenous changes shock the status quo’s efficacy (c).

**Proposition 2.1:** A low capacity or exposure policy maker (\( R_i \leq \gamma_i \frac{c_i^2}{3} \) (R inversely related to capacity)) is less likely to tailor.

**Proposition 2.2:** The more that the changed policy environment upsets its status quo policy (larger \( c_i^2 \)), the more likely a policy maker is to tailor.

### 6 Two Policy Makers: Sequential Decisions

The two player case is the heart of the social learning analysis. While quite simple, it helps us get at many of the important decisions a policy maker has to make and the decisions which lead to policy diffusion. This section produces intuitive, but previously under-investigated, propositions about who is more likely to learn from others and how they are likely to learn. This includes an enhanced understanding of how institutional capacity and issue complexity affect the propensity to learn from others. It also comprises a rigorous analysis of when actors are likely to mimic others, leading to the diffusion of virtually identical policies, and when they are more likely to modify a known policy leading the spread of similar, but different, policies.

**Players:** \( z_1 \) with ideal outcome \( o_1^* \), exposure parameter \( \gamma_1 \), and research cost \( R_1 \), and \( z_2 \) which has parameters similarly defined. The distance between their ideal outcomes is \( \Delta_{12} = |o_1^* - o_2^*| \)

**Sequence:** 1) The world changes. 2) Nature draws the realization of the policy map. 3) \( z_1 \) is selected to act first. 4) \( z_1 \) chooses the decision strategy to maximize its expected utility. 5) \( z_2 \) observes that \( z_1 \) has acted, and whether it has enacted a new policy. If it has, \( z_2 \) updates her beliefs about \( \psi \) and then chooses the decision strategy to maximize expected utility. 6) Policy choices, outcomes, and the associated utilities are realized.

**Analysis:** The basic solution concept is sub-game perfection. The choice sets are quite simple
for each player. Since \( z_1 \) acts first, its payoff is independent of \( z_2 \)'s actions in the second stage. Thus, \( z_1 \)'s behavior is exactly the same as that of the policy maker in the one player case. It simply chooses between research and maintaining the status quo. If \( z_1 \) maintains the status quo, \( z_2 \) learns nothing from it. It then also faces the same choice between research and maintaining its status quo policy.

The more interesting case occurs when \( z_1 \) researches and changes its policy and when \( z_2 \) gets to make its decision after at least another one other government has instituted a policy. This existing policy reveals information about the policy map. \( z_2 \) then approaches the policy choice after observing \( z_1 \)'s policy \( p_1 \) and its outcome \( o_1 = o_1^* \). It now has all four options available. First, we can focus on the interesting conditional tradeoffs between mimicking and modifying. We will then return to the other options to analyze the decision between independent research and learning from others.

The key question for government two is, when is modifying government one’s policy better than mimicking it? This is the tradeoff between a safe policy which produces another’s ideal outcome, and one which is closer to the policy maker’s own ideal in expectation, but with risk. The easiest way to solve for government two’s indifference between mimicking and modifying is to return to the optimal \( p_1^* \) equation (equation 7):

\[
p_2^* = p_1 + \frac{\Delta_{21}}{\mu} - \frac{\sigma^2}{2\mu^2}
\]

Because \( \mu \) and \( \Delta_{21} \) are positive by construction, \( p_2 \) must be greater than \( p_1 \). This is only true, and there is only a gain to modifying, when \( \frac{\Delta_{21}}{\mu} \geq \frac{\sigma^2}{2\mu^2} \). Thus, mimicking is preferred to modifying when:

\[
\Delta_{21} \geq \frac{\sigma^2}{2\mu}
\]  

(9)

Failing this conditions means that the best “modified” policy is actually one which is not altered at all. We can reach the same indifference condition by comparing equation 5 to equation 8. After rearranging we can see that the utility of the best modified policy is equal to the expected utility of the modifying option when \( (\Delta_{21} - \frac{\sigma^2}{2\mu})^2 = 0 \). Thus, when \( \Delta_{21} = \frac{\sigma^2}{2\mu} \), the best altered policy is one which is not altered at all. Substituting this into the best altered policy equation just leaves
As complexity increases, or \( \Delta \) decreases, modifying is no better than mimicking. Altering, or perhaps more precisely, altering more rather than less, is more attractive relative to following when the two governments’ goals are very different (large distance between them), and when issues are less complex (small \( | \frac{a^2}{\mu} | \)). The intuition is straightforward. A safe, existing, and well understood policy (following) looks less and less attractive when it was made to satisfy a vastly different policy maker’s goals (large \( \Delta_{21} \)). No matter how good an action is for government one, if it does not fit government two’s goals, then it is of less use. In practical terms, governments are relatively likely to borrow ideas more or less directly from similar “peers,” and more likely to alter when learning from less similar “non-peers.” Additionally, the more complex and uncertain an issue area is, the more can go wrong when modifying. In these cases, a well understood policy, even one known to be relatively distant from one’s ideal outcome, is relatively more attractive. The option to follow is akin to satisficing (e.g. Simon, 1978). The less one knows and the more one might err, the lower the “satisfactory” bar. Finally, note that the utilities of altering and following are deceasing with differences. Irrespective of which is better, all else equal, a government would rather learn from another that is similar to itself in whatever ways are relevant in a given application.

The preceding analysis has focused on the choice between mimicking and modifying. It has not yet considered the other two options. The policy maker acting second could eschew both options and either maintain the status quo invest in research to tailor. First, consider the decision between tailoring one’s own policy and learning from another’s. If mimicking is better than modifying, one will choose to research and tailor instead of mimic when \( R_2 < \gamma_2 \Delta^2_{21} \). If modifying is better than following, one will choose to research and tailor when \( R_2 < \gamma_2 [ \frac{a^4}{4\mu^2} - \frac{\Delta_{21} a^2}{\mu} ] \). In both cases, higher capacity governments (lower \( R \)) are more likely to tailor. Governments are less likely to tailor when they can learn from a similar and well informed peer (small \( \Delta \)). Altering will be particularly attractive relative to tailoring when the issue is less complex. In practice these decisions need not be dichotomous. Policy makers can consult multiple sources and use a variety of tactics. Thus, the analysis may often speak to the relative balance of independent and interdependent sources and influence in substantive applications.

Where tailoring is less attractive than the status quo, but where learning is more attractive than tailoring, the ability to learn from another will prompt some to move off of the status quo when
they could not have afforded to research on their own. Learning from others, either by following 
or altering, may be the only plausible policy making strategy for lower capacity governments. 
Additionally, there will also be instances in which tailoring is preferred to the learning options. 
For some, it may almost always be worth investing to get one’s ideal outcome. As before, the 
policy makers most likely to do their own research, no matter what others do, are those with the 
most capacity (smallest Rs), and the most at stake (large $\gamma$).

Finally, the analysis assumed that one actor was randomly selected to act first. In practice, 
an exogenous shock or unique circumstance may force one policy maker to face a decision early 
and force a government to invest $R_i$ to make new policy from scratch. Additionally, while the 
model assumes that those that do research will learn the full policy mapping with certainty, even 
if we were to relax this assumption (later in this chapter), the government that was forced by 
circumstance to confront an issue is probably the one most likely to approximate knowing all 
there is to know. These actors reveal the most useful policy information even though they may 
have made a mistake to make the issue important a salient in the first place. Proposition 3.1:

Higher capacity policy makers are more likely to research and tailor in lieu of learning from others 
$(R_i < \gamma_i \Delta_{i}^2 \text{ or } R_i < \gamma_i [\frac{\sigma^4}{2\mu^2} - \frac{\Delta_{ij} \sigma^2}{\mu^2}])$. Lower capacity policy makers are more likely to rely on 
learning from others.

**Proposition 3.2:** All else equal, whether mimicking or modifying, policy makers prefer to learn 
from those who have similar goals: (The expected utilities of mimicking $-\gamma_i \Delta_{ij}^2$, and modifying 
$-\gamma_i [\frac{\Delta_{ij} \sigma^2}{\mu^2} - \frac{\sigma^4}{4\mu^2}]$, are decreasing with $\Delta_{ij}$.

**Proposition 3.3:** Policy makers are more likely to modify when learning from another that is 
relatively dissimilar and when issues are less complex $(\Delta_{ij} \geq \frac{\sigma^2}{2\mu})$. They are more likely to 
mimic when learning from another that is more similar and when issues are more complex 
$(\Delta_{21} < \frac{\sigma^2}{2\mu})$.

**Proposition 3.4:** Others will frequently follow or alter from policy makers that have direct 
experience with issues, often due to forces outside of their control.
6.1 Informational Availability and Learning

Thus far, the theoretical analysis has largely set aside variation in the amount of information available. Proposition 2.3 above, and the general analysis of complexity, relate to this type of variation. This proposition, and the theoretical approach more generally have implications for variation in the rationality of learning as a function of the amount of policy information available. That is, we can easily extend the logic to variation across policy issues and areas (Nicholson-Crotty, 2009; Volden and Makse, 2010). The less policy information is available, the more learning and following we should observe. Similarly, when others, particularly authoritative sources of policy information such as courts, agencies, the federal government, or supra-national organizations provide concrete policy guidance we should see less learning from others. In cases in which more policy information is available, we should find less support for the learning propositions derived above and below.

**Proposition 3.5 - Inter-Issue Informational Availability:** The importance of learning from others, and thus evidence in support of the other propositions, should increase when there is less other policy guidance available.

6.2 Application to Third Party Policy Solutions

The same logic applies when industry associations or other third parties proffer policy ideas or model policies. There is still an existing policy idea to follow (or alter), and others’ likelihood of doing so will depend on the same variables as it would if the policy came from another actor that is actually facing the problem. An organization which is offered the opportunity to adopt a third party policy idea will have to consider the likelihood that the policy is designed to achieve goals similar to its own. While some of the details, particularly notions of similarity, may be slightly different, the basic story remains the same. As when other institutions have acted, when a third party proffers a policy solution, there are plenty of circumstances in which it will influence others. This is more likely when it comes from an association expected to represent the institutions’ goals and interests.
6.3 Two Policy Makers: Simultaneous Decisions

For the most part, assuming sequential decisions is reasonable. When a government acts, frequently there will be others that have already acted offering opportunities for learning. The problematic equilibrium where all wait hoping for someone to follow is a separate problem which is not analyzed here. Additionally, this problem is usually not a concern because there are plenty of reasons why some would act early. For example, exogenous factors, interest group activity, issue entrepreneurs, and other factors might prompt some to act earlier than others. Moreover, those with the most capacity may tailor no matter what and might not have any incentives to wait. More precisely, assuming that policy makers simultaneously decide whether to research or wait and see, and then policies and outcomes are observed, the potential for free riding is often not a major concern. Three of the four permutations in the simultaneous model collapse to those in the sequential setup. If, for example, one government will either always tailor or never tailor in a particular policy context, then the players are in one of the permutations of the sequential case. The fourth permutation, the one that is a bit different, occurs when there are two (or N in a generalization) actors who would tailor if they had to, but who would prefer to free ride off of another’s research. In this case, the players will play mixed strategies to keep each other honest as in other public goods models. These questions of strategic delay to wait for opportunities to use “diffusion” tactics and strategic behavior on the part of early adopters to enable (or disable) others following them are interesting and important questions but are secondary to this paper’s focus.

7 Three Policy Makers and Imperfect Learning

Thus far, the analysis has assumed that there is only one other government to learn from. It has also assumed that those who research and implement custom policies perfectly achieve their ideal outcomes. Under this second assumption, policy-outcome pairs are exactly what actors think they are. This section relaxes these assumptions. First, it considers an actor choosing one of two other policies to learn from. This analysis introduces noise into the observations of policies and outcomes to consider the tradeoffs between similarity and competence. Obviously assuming that a government can invest in research to craft a perfect policy to meet its goals is unrealistic. Other research suggests that the likelihood that a policy is actually effective affects its likelihood...
of diffusing. In the model, deviating from diffusion as “emulation” (e.g. Shipan and Volden, 2008), I assume that policy makers infer a policy’s likely effectiveness at meeting the goals it is supposed to meet by looking at the policy’s source rather than by observing its long run quality in practice. More concretely, capacity not only affects one’s propensity to make policy independently but it also affects one’s ability to do so effectively and thus others’ propensity to learn.

These considerations are particularly relevant when one’s peers are less expert and more likely to err than higher capacity non-peers. Next, it considers how actors can learn from two other policies by forming more precise beliefs about policies and outcomes using a “Brownian bridge” (Callander, 2010). Incorporating imperfect learning and learning from multiple policies advances the literature in a few ways. For one, it allows us to consider how the traits of one policy maker (e.g. its capacity) affect the likelihood that others will follow its policies. More generally, it points to which policies are more likely to diffuse when later adopters have multiple models to choose from. Additionally, analyzing the possibility of learning from multiple other policies is also a substantial innovation to the literature which mostly focuses on choices about whether or not to adopt one particular policy.

7.1 Imperfect Learning

To this point, a policy maker could infer the relationship between a policy \( p_j \) and its outcome \( o_j \) perfectly. To relax this assumption, I now assume that one may err when implementing a policy after tailoring. This produces noise around the signal of the relationship between a particular policy and its associated outcome. Under these new assumptions, the actor observes a signal of its optimal policy-outcome pair, but it mistakenly implements a different policy which it thinks produces its ideal outcome. Now, the relationship between a policy and its outcome is noisy even after tailoring. These imperfections will vary from actor to actor. Those with more capacity might make fewer errors when they invest to tailor their own policies. This description captures many important real world variations.

Formally, \( p_j \) (which is perfectly observed) produces outcome \( o_j + \epsilon_j \) where \( \epsilon_j \) is normally distributed with mean zero and variance \( \tau_j^2 \). (The expected magnitude of \( \epsilon_j \) is \( \tau_j \sqrt{2/\pi} \)). This noise varies by policy maker, its distribution is common knowledge, and it is a trait of the implementer (the early adopter), not the observer (hence the j subscript). Some (e.g. high capacity) learn
more precisely than others. $\epsilon_j$ will be zero for those that do learn perfectly as in the previous cases modeled. The actor makes its best effort to implement $p_j$ to produce $o_j^*$, but it may actually achieve a sub-optimal outcome $o_j \neq o_j^*$.

The outcome it achieves is now the new random variable $O_j$ which is equal to the sum of the standard policy mapping function $\psi(p)$ and the additional noise ($O_j = \psi(p_j) + \epsilon_j$). There are now two sources of uncertainty: the variance in the policy mapping function, and the variance of the imperfect learning. I denote the combined variance, the variance of $O_j$, $S_j^2 = \sigma^2 + \tau_j^2$ where $\sigma^2$ is the Brownian motion variance and $\tau_j^2$ is the variance of actor-specific implementation error.\(^5\)

Incorporating imperfect learning changes the expected utility of both mimicking and modifying. Recall, in general the expected value of a tactic is $-\gamma_i E[(O_j - o_i^*)^2]$. Thus, the expected utilities of the two tactics are:

\[
EU_i(\text{mimic}_j) = -\gamma_i \Delta_{ij}^2 - \tau_j^2
\]

\[
EU_i(\text{modify}_j) = -\gamma_i \left[ \frac{\sigma^4}{4\mu^2} - \frac{\Delta_{ij} \sigma^2}{\mu} - \tau_j^2 \right]
\]

The derivations of both are very similar to those in the two player game (above in more detail) except that they include the additional uncertainty from $\tau_j^2$. We can now consider the case where two policy makers have tailored but with different precisions. A third can choose which of them to learn from.

### 7.2 Choosing One of Two Sources Under Imperfect Learning

**Players:** $z_1$, $z_2$, and $z_3$ with parameters defined as above. From the perspective of actor one, there are now two relevant difference parameters. The first, $\Delta_{12}$ is the goal similarity between itself and policy maker two. The second, $\Delta_{13}$ is the goal similarity between itself and policy maker three. Additionally, to incorporate different learning precisions, assume that $z_3$ implements its ideal outcome after tailoring (no noise, $\tau_3^2 = 0$), and $z_2$ implements with expected error $\epsilon_2$ as

\(^5\)This implicitly assumes that there is a delay in realizing the true utility a policy produces which seems especially reasonable in complicated policy choices.

\(^6\)This observation error does not affect the increments of the Brownian path. It is not variance in the Brownian motion. It is variance in one’s estimate of the value of $\psi(p)$ at some value of $p$.\]
above. \( z_2 \) is less informative while \( z_3 \) is more expert. Also, assume that both \( z_2 \) and \( z_3 \) act early and tailor policies before \( z_1 \) acts.

**Sequence:**
1) The world changes.  
2) Nature draws the state of the world - the realization of the policy map and the observation error \( \epsilon \).  
3) Actors observe that the policy map is a Brownian motion with drift \( \mu \) and variance \( \sigma^2 \).  
4) \( z_2 \) and \( z_3 \) act early and invest to tailor.  
5) \( z_1 \) observes that both \( z_2 \) and \( z_3 \) have tailored and chooses which to learn from and how to learn from them.  
6) Policies, outcomes and utilities are realized.

**Analysis:** The difference between the utility of mimicking \( z_2 \) and the utility of mimicking \( z_3 \) is a simple tradeoff between goal similarity and precision. Since there is only utility lost from the observation error when learning from policy maker two, following the imperfect learner \( z_2 \)’s policy is preferred to following \( z_3 \), the perfect learner, when

\[
-\Delta_{12} - \epsilon_2^2 \geq -\Delta_{13} \quad \text{or when:}
\]

\[
\Delta_{13} - \Delta_{12} \geq \epsilon_2^2 \quad \text{(12)}
\]

The difference between the utility of modifying \( z_2 \)’s and \( z_3 \)’s policies is slightly more complex. Modifying the imperfect learner’s policy (\( p_2 \)) is preferred to modifying \( p_3 \), the perfect learner’s, when

\[
-\gamma_1 \frac{\sigma^4}{\mu^2} - \frac{\Delta_{12} \sigma^2}{\mu} - \epsilon_2^2 > -\gamma_1 \frac{\sigma^4}{\mu^2} - \frac{\Delta_{13} \sigma^2}{\mu} \quad \text{or, after rearranging, when:}
\]

\[
\frac{\sigma^2}{\mu} [\Delta_{13} - \Delta_{12}] > \epsilon_2^2 \quad \text{(13)}
\]

To analyze these tradeoffs we must consider two possible cases: *Either policy maker three, which is more informed, is also more similar to policy maker one than policy maker two is, or policy maker two is more similar:*

1. Policy maker three (\( z_3 \)), which learns without errors, is **more similar** to policy maker one (\( \Delta_{13} \leq \Delta_{12} \)). At least in a relative sense policy maker three is a “peer” and policy maker two is a “non-peer.”
   - If policy maker three is at least as similar to policy maker one as policy maker two is, policy maker one will always learn from policy maker three. The left side of the condition for learning from policy maker two (equation 12 or 13) will always be negative if \( \Delta_{13} < \Delta_{12} \) and the condition will be unachievable. Simply and intuitively,
if the more similar policy maker is also more informed, learn from the more similar policy maker.

2. Policy maker three ($z_3$), which learns without errors, is less similar to policy maker one than policy maker two is ($\Delta_{13} \geq \Delta_{12}$).

- If policy maker two is less similar, policy maker one faces a choice between learning from a less informed peer or a more informed non-peer. This situation may arise frequently in practice. If, for example, larger, more professional policy making bodies are well informed, smaller ones will face choices between learning from their expertise, and learning from those who may have more similar characteristics and goals. In this case, a government will prefer to modify from a peer according to the condition in equation 13 (or 12 in the case of mimicking). The likelihood of modifying from the less informed peer is increasing in the similarity gap between the two (large $\Delta_{13} - \Delta_{12}$), increasing with increases in the peer’s learning precision (small $\tau_2^2$), and increasing in the issue complexity (large $\sigma^2 / \mu$).

- The intuition is relatively straightforward. When non-peers are very different, or peers are reasonably well informed, learn from peers. When one’s goals are reasonably close to a non-peer’s or when a non-peer has a large expertise advantage over a peer, learn from non-peers. These relationships are a bit tricky because they may be negatively correlated. The noise with which the lower capacity learners implement policies may increase in the complexity of the issue. The high capacity non-peers who are more informed may be especially well informed on those issues so “all else equal” tradeoffs may be relatively rare in this instance.

**Proposition 4.1:** Policy makers with high capacity peers to learn from will not learn from lower capacity non-peers (equations 12 and 13 cannot be satisfied when $\Delta_{13} < \Delta_{12}$).

**Proposition 4.2:** The likelihood of learning from (equation 12 or 13) a less informed peer (relative to a more expert non-peer) will increase, all else equal, with the relative dissimilarity of expert non-peers ($\Delta_{13} - \Delta_{12}$), with the relative precision of the peer’s learning (smaller $\tau_2^2$), and with issue complexity ($\sigma^2 / \mu$, altering only).
7.3 Learning From Two Policies

In the previous section, policy makers had to choose which other actor’s policy to learn from. This analysis offered insight into the tradeoffs between goal similarity and expertise. This section considers how one can learn from multiple existing policies. In practice, governments and other policy makers rarely have to choose one and only one other government to learn from. Knowing more than one policy-outcome pair can help an actor triangulate and better identify her optimal action in some cases. More precisely, knowing two points which span one’s ideal (one outcome on the left and one on the right) allows one to construct a “Brownian bridge” in which the noisy policy map is “tied down” at two endpoints (Callander, 2010). While a “Brownian bridge” is technical, the intuition is very accessible. For example, knowing what policies a more liberal state and a more conservative one have adopted in a particular area can offer more information to a moderate state than only observing one of their policies. Because Brownian motion is a Markov process, knowing two points only provides additional information for estimating the function’s value between them. The conditional expected value and precision of beliefs on the flanks is the same as if one only knew the closer endpoint (Callander, 2010). Such beliefs are “open ended” just like those in all of the previous analyses when only one point was known.

Brownian bridge analysis is central to Callander’s (2010) analysis of policy experimentation. I apply it here to learning from others, but the ideas are very similar. The government’s decision to experiment and change its own policy in his paper parallels the decision to modify another’s policy in the diffusion context. Consider \( z_1 \)’s behavior when \( z_2 \) and \( z_3 \) have already acted, researched, and implemented policies to achieve their ideal outcomes \( o_2^* \) and \( o_3^* \) respectively. Assume that, as in figure 2, \( z_1 \)’s ideal outcome is 0, that \( o_2^* \) is negative, and that \( o_3^* \) is positive (\( o_2^* < o_1^* = 0 < o_3^* \)) such that the two known outcomes span \( z_1 \)’s ideal. Also assume that \( z_2 \) and \( z_3 \) implement their ideal policies precisely (\( \tau_2^2, \tau_3^2 = 0 \)). Lastly, assume that \( z_2 \) has more similar goals (\( \Delta_{12} < \Delta_{13} \)). \( z_1 \) knows that the Brownian path passes through \( o_2^* \) and \( o_3^* \) and proceeds with the expected variation between them. These new constraints on the path allow for updated, and more precise, beliefs about the policy map for policies along the bridge. The conditional expectation and variance for a policy \( p_1 \) spanned by the bridge are:
Expected Outcome: $E[\psi(p_1)] = o_2 + M(p_1 - p_2)$ \hfill (14)

Variance: $var[\psi(p)] = \frac{(p_1 - p_2)(p_3 - p_1)}{(o_3 - o_2)} \sigma^2$ \hfill (15)

Figure 2: The figure provides an example of learning from two policies using a Brownian bridge. The bridge allows beliefs about the local slope between two known points which are more precise than beliefs based on the overall drift of the motion.

$M$ is the slope of the line segment connecting the two ends of the bridge $(\frac{o_3 - o_2}{p_3 - p_2})$. Knowing two ends of the bridge provides information about local slope (and the conditional expectation of outcomes) which is more precise than the overall drift parameter $\mu$. The expected value of the function along the bridge is the linear interpolation between the two endpoints. The variance is a fraction of the overall Brownian motion variance. Because one knows the endpoints for sure, the variance is zero at either end. It peaks halfway between them. Because knowing two points reduces uncertainty between them, it will increase the propensity to modify when one’s ideal outcome is between two known points.

To investigate how the bridge affects the mimic or modify tradeoff, we can take the derivatives of the expression for the expected utility along the bridge to identify the conditions for modifying. With an ideal outcome $o_1^* = 0$ (and assuming $\gamma_1 = 1$ for simplicity), the expected utility, and its derivatives, of a policy $p_1$ is:
\[
EU_1(p_1) = -[o_2 + M(p_1 - p_2)]^2 - \frac{(p_1 - p_2)(p_3 - p_1)}{p_3 - p_2}\sigma^2
\]
\[
\frac{dEU_1(p_1)}{dp_1} = -2M[o_2 + M(p_1 - p_2)] - \frac{p_2 + p_3 - 2p_1}{p_3 - p_2}\sigma^2
\]
\[
\frac{d^2EU_1(p_1)}{dp_1^2} = -2M^2 + 2\frac{\sigma^2}{p_3 - p_2}
\]

Modifying to make new policy along the bridge is preferred to mimicking the closer end point \((p_2, o_2)\) by construction) when the second derivative is negative (implying a unique optimal policy), and the first derivative is positive at \(p_2\) (implying that the endpoint \(p_2\) is not this unique optimum). The second derivative is negative when \(p_3 - p_2 > \frac{\sigma^2}{M^2}\). Because \(M = \frac{o_3 - o_2}{p_3 - p_2}\), the second derivative is negative, and there is a unique optimal policy when \(o_3 - o_2 > \frac{\sigma^2}{M}\). With \(o_1\) equal to 0, \(o_2\) negative, and \(o_3\) positive, \(o_2\) and \(o_3 = -\Delta_{12}\) and \(\Delta_{13}\) (the goal similarity measures) respectively. Thus, there is a unique optimum along the bridge when:

\[
\Delta_{13} + \Delta_{12} > \frac{\sigma^2}{M}
\]

This condition is easier to meet when the bridge spans (the sum of the \(\Delta_s\)) a wider range of outcomes and when the complexity along the bridge is relatively low (\(\frac{\sigma^2}{M}\) is similar to \(\frac{\sigma^2}{\mu}\) earlier). While \(\sigma^2\) is an invariant property of the policy-map, the slope of the bridge will increase, and the complexity will thus decrease, with the magnitude in the change of outcomes relative to the magnitude of the change in policies. When outcomes change rapidly with policies, the bridge, and knowing a second policy-outcome pair, becomes more informative. When this condition is satisfied there will be a unique altering solution as long as the first derivative is positive at \(p_2\).

This insures that the optimal “modified” policy is not actually just the “mimic” policy \(p_2\). With \(p_1 = p_2\), the first derivative is \(\frac{dEU_1(p_1=p_2)}{dp_1} = -2M[o_2 + M(p_1 - p_2)] - \frac{p_2 + p_3 - 2p_1}{p_3 - p_2}\sigma^2\) which reduces to \(-2o_2M - \sigma^2\). This expression is positive, and there is an optimal modified policy along the bridge, when \(\Delta_{12} > \frac{\sigma^2}{2M}\) or \(2\Delta_{12} > \frac{\sigma^2}{M}\).

The first and second derivative conditions are very similar. Since \(\Delta_{13} + \Delta_{12} > 2\Delta_{12}\) by construction, the first derivative condition will be the constraint. We can compare it to the modifying condition we derived earlier when only one policy-outcome pair was known. In that case, modify-
ing was preferred to mimicking when \( \Delta_{12} > \frac{\sigma^2}{\mu} \). We can see that all else equal, the bridge doubles the likelihood of modifying through the 2 on the left hand side. Additionally, the bridge will increase the likelihood of modifying when it reduces complexity. Since \( \sigma^2 \) is constant, the bridge will reduce complexity when its slope \( M \) is steeper than the overall drift \( \mu \). More intuitively, when a policy maker observes two relatively similar policies producing vastly different outcomes she has a lot to gain from modifying and choosing a new policy between the two. Additionally, since having an ideal outcome along the span will make one more likely to modify, those with middle of the road goals will be more likely to modify. Those on the extremes will be more likely to mimic a relatively close known policy. Finally, and intuitively, the optimal policy (which we can identify by setting the first derivative to zero and rearranging into a messy expression) and outcome along the bridge will be closer to \((p_2, o_2)\) than to \((p_3, o_3)\) (Callander, 2010).

**Proposition 5.1**: All else equal, knowing a second policy-outcome pair will double the likelihood of modifying vs. mimicking relative to knowing only one policy-outcome pair. After observing two pairs of policies and outcomes \((p_2, o_2)\) and \((p_3, o_3)\) with certainty, a policy maker with an ideal outcome between the two of them will enact a modified policy when \( 2\Delta_{12} > \frac{\sigma^2}{M} \). \( M \) is the slope of the line segment connecting the two points and \( \Delta_{12} \) is the goal difference from policy maker two which is a more similar peer.

**Proposition 5.2**: The larger the difference in two known outcomes when one is on each side of a policy maker’s ideal, the more likely the policy maker with moderate goals is to modify rather than mimic.

### 8 Discussion: Implications for Empirical Research

In this case, deductive theory does two things for empirical research. First, as theory is supposed to do, it points to specific associations and regularities that empirical research can test. Many of these implications of the model are quite intuitive, at least in hindsight. Nevertheless, few, if any, of them have been investigated in systematic ways before. Despite the rather large diffusion literature, we still know very little about, for example, the conditions under which one would mimic another’s policy and when one would modify it. The model points to a number of likely
empirical realities which would each broaden and deepen our understanding of policy diffusion. The second thing theory does in this instance is more general. The model suggests that there are substantial limits and limitations to conventional empirical diffusion methods. Almost all empirical work focuses on the diffusion of particular policies. The model suggests, among other things, that future empirical work should focus on diffusion, or lack thereof, in particular policy areas. This section describes some of the model's implications for empirical research. Before describing concrete applications it elaborates on the broader implications for empirical methods in policy diffusion studies. It then details some empirical implications which roughly fit with current methods and some implications which are testable with other empirical approaches.

The model and its empirical implications are very general. It largely speaks to the content of policies rather than their existence. Unlike in most other diffusion work, “adopt or do not adopt” is not the model’s primary question. The model’s predictions are applicable, at least in spirit, to a variety of policy making situations. These applications range from policy innovations such as smoking bans and curricular standards in U.S. cities and states to the implementation of intellectual property and environmental treaties around the world, to banks’ compliance with vague financial regulations. The flexible model gives empirical researchers decisions to make in applying it. Many of these decisions concern the substantive conceptualization of the policy-outcome uncertainty. In some cases, the uncertainty may be political uncertainty as policy makers may be unsure of how a policy will resonate with voters. In other cases it may be effectiveness uncertainty such as how much innovation and/or rent seeking an intellectual property regime will produce. The formalization is flexible enough that ideal points could actually represent a balance between policy outcomes and political ones. Finally, in other cases the researcher may have to combine policy-outcome uncertainty with a separate variable to address political popularity and reelection concerns. In this way the model would be a substitute for the “external determinants” component of some empirical diffusion models.

In nearly all existing studies, the investigator picks one policy (or a very small number of policies) which she knew became popular. She then investigates the traits of the adopting and non-adopting policy makers to test and identify variables that affect the likelihood of adopting the policy of interest. The theory strongly implies that trying to model the variables that affect a policy maker’s propensity to adopt a particular policy which is known to have become popular
can only get us so far. Some of the important action in policy diffusion manifests in the policies that spread along with those that do not spread. Identifying these types of variation along with understanding some of the other mechanics of policy diffusion requires deviating from current methods and types of data.

For example, empirical work should move away from selecting on policies and instead select on policy areas. Selecting a policy area in which one expects policy action due to exogenous shocks, new technologies, or salient crises, but without knowing exactly which policies governments enacted in this policy area, would be very fruitful. One could then identify the universe of plausible options based on the early adopters and see which of these policies diffuse and which do not as a function of the early adopters’ traits such as capacity and similarity. Additionally, policy diffusion is an area which could benefit from supplementing large N studies using observational data with self-report data about policy making processes. Diffusion is a process and the outcome data that empirical work can observe are, at best, imperfect indicators of the process. Understanding diffusion mechanisms requires getting inside policy decisions. Methods such as interviews and surveys can better capture detailed information about which inputs (e.g. which other governments’ policies) were influential in a policy making process and when policy makers relied more on independent analysis.

While it suggests some new empirical approaches, some of the model’s implications are indeed testable in roughly the same ways that existing policy diffusion variables have been tested. That is, they can be included in event history models as independent variables that affect an actor’s likelihood of enacting a policy given the others that have enacted it. Some of these potential investigations would also require measures of goal similarity such as placing each actor’s likely goals onto a one-dimensional scale (less-more, liberal-conservative etc.). For example, one of the model’s implications is that high capacity policy makers’ choices may influence both their peers’ policy choices as well as less similar lower capacity actors’ policies whereas lower capacity policy makers are likely to only influence their peers. Roughly speaking, California adopting a policy should affect New York and New Hampshire which is very different and has a non-professional legislature whereas Vermont should only affect New Hampshire. This effect should show up in the interaction between the capacity of previous adopters and the similarity between them and subsequent policy makers. Similarly, we should see higher capacity governments’ adoptions lead
to adoptions by ostensibly different lower capacity governments when their issue specific policy
goals are likely relatively similar.

Another set of implications fit into the current methods but require comparing adoption pat-
terns across multiple issues. A lot of the important, but previously underappreciated, variation
is in the policy making context. For example, the model predicts that adoption by governments
with similar goals should increase another’s propensity to adopt. Moreover, similarity should lead
to more adoption when issues are more complicated. Thus, if one had data comparing the same
set of actors across multiple policies, one should see an interaction between an issue’s complexity
and a goal similarity between early and later adopters. For example, one could code the practical
details of countries’ implementations of flexible treaties in areas such as environment, security,
and intellectual property. We should see both similarity effects as well as similarity-complexity
interaction effects across the issues.

Finally, the Brownian bridge analysis of learning from multiple actors has implications for dif-
fusion via imitation. While some of these propositions might only be identifiable in a laboratory
setting, the unique analysis of learning from others has at least one application to more conven-
tional diffusion methods. The analysis implies that having others with policies to learn from on
both sides of one’s goals increases the likelihood of modifying. By extension, policy makers who
likely have more extreme policy goals are more likely to imitate a reasonably close policy since
they will not have opportunities to observe others’ policies which span their goals. For example, a
state seeking a drunken driving law that balances treatment and punishment can observe a treat-
ment intensive state and punishment intensive state and then confidently enact a modified policy
between them. A state seeking a harsh punishment policy only (with no treatment component) is
more likely to simply imitate a punishment intensive policy. If one is investigating the diffusion of
one particular and specific policy via imitation, one should see, all else equal, actors with relatively
extreme goals more likely to imitate. Since those with more moderate goals are more likely to
modify they are less likely to enact the exact policy of interest.

Some of the other implications are testable with methods different from those usually found in
empirical diffusion studies. One of the most important is that diffusion will affect lower capacity
policy makers (usually smaller states, cities etc.) more than it will affect higher capacity ones.
The latter are more likely to make more independent choices via “tailoring.” In absolute terms
higher capacity policy makers might use both types of sources more than lower capacity ones. They have more time, staff, and other resources to collect all sorts of policy making information. Nevertheless, in terms of influences on a given policy decision, or influences on an average policy decision, we should see lower capacity policy makers rely relatively more on diffusion while higher capacity policy makers rely relatively more on independent customized policies. More concretely, if one could measure the impact of sources’ influence on policy decisions, others’ policies should compose more of the total influence for lower capacity actors. In contrast, sources consistent with independent policy making such as experts, consultants, quantitative studies, predictive analysis, and others, would matter more for higher capacity governments.

One way to investigate this implication, recognizing that dissecting the reasons behind policy choices is tricky, would be to use interview or survey data. Many policy makers are likely happy to describe the decision processes and the sources of information behind important policies in relatively accurate detail. The important part of these descriptions would be the importance of various sources and policy making tactics. Additionally, in some cases where policy inputs are publicly observable one might be able to do a similar analysis using observational data. For example, one could examine the content of committee hearings in legislatures or school boards and observe how often others’ policies are mentioned compared to how often sources such as expert consultants and original research are part of the policy making history.

Another set of important implications follows from the optimal modifying condition and from the tradeoffs between mimicking and modifying. One of these implications is that, all else equal, modified policies should be more similar to the original policy they are based on in more complex policy realms. This implication speaks to important substantive questions such as how much early adopters’ decisions will influence others’ policies and how much “misfit” policies made via diffusion will exhibit. This implication is testable on individuals in the lab. One only needs to vary the complexity of a decision after giving a participant another’s policy choice and the outcome it produced. Participants’ policies should be closer to the one given to them when the decision task is more difficult and less certain.

This variation is also potentially measurable in observational data. This implication is a good example of the benefits of shifting from focusing on the diffusion of one particular policy to focusing on diffusion in a policy area. For example, to look for evidence of optimal modifying as a
function of issue complexity one could pick two policy areas, such as renewable energy incentives and welfare, and collect each state’s policy and the time it was implemented. Now, instead of looking for adoptions of one particular policy in these areas one would be looking at the variation in policy choices. All else equal, one should see more variation around the first (or perhaps most high profile) policy in the less complex policy areas as governments will be more willing to modify these policies by larger amounts when outcomes are more certain. This same approach could also test the predictions concerning capacity and tailoring. Given a set of policies it is more likely that a higher capacity later adopter should adopt a policy which is more deviant from the others. This follows from the logic of tailoring since higher capacity governments are more likely to tailor a custom policy and less likely to rely on learning from others’ policies.

9 Conclusion

The model above advances our understanding of learning, diffusion, and policy interdependence. The targeted learning theory deviates from relatively mindless notions of copying and policy diffusion which lack micro-foundations, underestimate policy makers’ rationality, and do not generate systematic predictions. It also differs from learning models that make heroic assumptions about actors’ ability to observe and process all there is to know and learn about complex, multi-dimensional, issues. The model does this by combining a number of attributes of learning and decision making that have been absent from previous theories with findings from previously unconnected empirical work. Among these advances are its use of Brownian motion to model signals which are always partially invertible and vary in complexity, its use of continuous policy options and goals, its analysis of mimicking and modifying, and its focus on the impact of variations in goal similarity and capacity. This theoretical work has implications, both broad and narrow, for future empirical work in a variety of subfields and substantive applications.

In the theory, as long as a policy maker knows who is likely to know what they are doing, and how similar she is to these other actors, she can learn rationally even under capacity and information constraints. This requirement is more plausible than stronger information assumptions. Policy makers often know more about other policy makers than they do about particular policy areas. While we all have comfortably made choices when we were able to follow a perfect proxy, a
friend who shares our goals and is well informed for example, important decisions will often require tradeoffs between learning from one who is more similar and learning from one that is more likely to find a policy to meet its own goals well.

The theory focuses on the strategies and sources of information that organizations will use given a set of institutional and situational traits. It suggests that not only may a relatively small set of actors devise original policies which others will learn from, but that these patterns of influence will be predictable. Thus, the model speaks to the content of policies in ways that other diffusion work that focuses on dichotomous adoption choices does not. These predictions should also begin to help distinguish targeted learning from both independent policy adoption, and other diffusion mechanisms. For example, capacity differences should matter less if all actors independently adopt similar policies or if they follow each other for legitimacy or coordination reasons. Additionally, policy makers will not think in targeted or nuanced ways about similarity considerations, and about altering vs. following, if they are mimicking others to maintain legitimacy, or to gain benefits from coordination. Of course, these different diffusion mechanisms can still point in the same direction and share co-variates. While the theory above is a step toward parsing and identifying the synergies between mechanisms, there is much more to understand about how and why policy choices often appear to be interdependent. Thus, in addition to suggesting future empirical work, the model also points toward future theoretical work. This work should include incorporating other diffusion mechanisms, such as commonality or legitimacy preferences, or competitive dynamics, into the framework above.

The model above, along with extensions to beyond it, should help advance the rapidly expanding diffusion literature. This model and the literature in general help us better understand how actors respond to available information by learning from others to do the best they can when facing challenging decisions. While these situations and actions are intuitive and familiar to many of us from our own experiences making decisions, our general and systematic understandings of them are still limited but increasing rapidly.
Appendix

Derivation of Expected Utility and Optimal Modified Policy

\[ EU_i(\text{modify}_{ij}) = -\gamma_i[(o_i^* + \mu(p_i - p_j) - o_j^*)^2 + |p_i - p_j|^2] \]

Without loss of generality, assume that \( \mu \) and \((o_i^* - o_j^*)\) (the distance \( \Delta_{ij} \) between i and j’s ideal outcomes) are positive. Thus, the expected utility of implementing policy \( p_i \) which produces outcome \( o_i = \psi(p_i) \) after observing that \( \psi(p_j) = o_j^* \) is:

\[ EU(p_i) = -\gamma_i[\mu(p_i - p_j) - \Delta_{ij}]^2 - \gamma_i(p_i - p_j)^2 \tag{17} \]

The optimal altered policy is denoted \( \dot{p}_i^* \). We solve for it by finding the \( p_i \) that maximizes equation 17. The derivatives with respect to \( p_i \) are:

\[ \frac{dEU}{dp_i} = 2\mu\gamma_i[\Delta_{ij} - \mu(p_i - p_j)] - \gamma_i\sigma^2 \]
\[ \frac{d^2EU}{dp_i^2} = -2\gamma\mu^2 \]

Setting the first derivative to zero to solve for \( \dot{p}_i^* \):

\[ \dot{p}_i^* = p_j + \frac{\Delta_{ij}}{\mu} - \frac{\sigma^2}{2\mu^2} \tag{18} \]

We can then solve for the expected utility of altering by implementing the optimal \( \dot{p}_i^* \). We substitute \( \dot{p}_i^* \) from equation 18 into equation 17 to get:

\[ EU(\dot{p}_i^*) = -\gamma_i[\mu(p_j + \frac{\Delta_{ij}}{\mu} + \frac{\sigma^2}{2\mu^2} - p_j) - \Delta_{ij}]^2 - \gamma_i[\mu(p_j + \frac{\Delta_{ij}}{\mu} - \frac{\sigma^2}{2\mu^2} - p_j)]\sigma^2 \]
\[ EU(\dot{p}_i^*) = -\gamma_i[\frac{\sigma^2}{2\mu^2}]^2 - \gamma_i[\frac{\Delta_{ij}}{\mu} - \frac{\sigma^2}{2\mu^2}]\sigma^2 \]

Thus, the expected utility of implementing the best altered policy after learning one policy-outcome pair is:

\[ EU(\dot{p}_i^*) = -\gamma_i[\frac{\Delta_{ij}\sigma^2}{\mu} - \frac{\sigma^4}{4\mu^2}] \tag{19} \]
References


